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Abstract

The industrial exploitation of microalgae is characterized by the production of high value compounds. Optimization of the performance of microalgae culture systems is essential to render the process economically viable. For raceway systems, the task of optimization is rather challenging since the process is by essence periodically forced and, as a consequence, optimization must be carried out in a periodic framework. In this paper, we propose a simple operational criterion for raceway systems that when integrated in a strategy of closed-loop control allows to attain biomass productivities very near to the maximal producitivities. The strategy developed was tested numerically by using a mathematical model of microalgae growth in raceways. The model takes into account the dynamics of environmental variables temperature and light intensity and their influence on microalgae growth.

Keywords: control, microalgae, modeling, optimization, photobioreactors, raceway

1. Introduction

Microalgae assimilate inorganic carbon through photosynthesis, a process that takes place in two phases, namely light-dependent stage (light reactions) and light-independent stage (dark reactions). The second phase comprises a series of reactions catalyzed by the enzyme ribulose bisphosphate carboxylase oxygenase (RuBisCO). In this phase, CO_2 is incorporated into organic material, leading to the formation of the carbon building blocks that are further synthesized into carbohydrates, proteins, lipids and nucleic acids [38].

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Due to its biochemical properties, microalgae have been raised as promising feedstocks for the production of high value compounds. The commercial use of microalgae includes applications in food industry and cosmetics [35]. Moreover, microalgae have been identified as a renewable source for biodiesel production [5, 18]. However, despite these favorable characteristics, microalgae production in a sustained and large scale basis is probably carried out far from an optimal working mode. Here, we mainly refer to the technology of raceways (high rate open ponds), which are nowadays the systems generally used for large microalgae production.

The difficulty of achieving optimal productivities of microalgae in outdoor systems results from the high interaction of phenomena that take place during growth and the low level of control that we have on them. This factor makes the whole process inefficient under an environment that is fluctuating by nature. The challenge of optimizing microalgal culture systems is a broad endeavour that includes reactor design [24, 32] and strain selection [33]. Furthermore, once the reactor configuration and the microalgal strain have been chosen, optimal performances can be achieved by acting on operational variables, such as temperature, pH and nutrient feeding rate. In this aspect, mathematical models offer a powerful tool to be exploited. Indeed, optimization can be model driven. Since microalgal metabolism is mainly influenced by nutrient availability, light intensity and temperature, several models have been developed to account for these factors [8, 14, 15, 29, 26, 3]. A work of synthesis has been performed to provide a mathematical model that incorporates the main factors that influences microalgal dynamics by keeping a relative simple structure [2] that might be suitable for control processes.

The task of bringing a process close to optimality by acting on the inputs of the system is the realm of optimal control. The optimal control problem that we are considering consists in finding the time evolution of the manipulated variables maximizing a given criterion on a finite time horizon. This problem can be solved by indirect methods such as the Pontryagin's maximum principle or by direct methods (numerical optimization). The advantage of using Pontryagin's maximum principle is that of providing an analytic solution. In this respect, a theoretical study on a simplified model of microalgae growth provided guidelines on the form of the controller to reach an optimal productivity [16].

This study was the first dedicated to optimal control of microalgae in a periodically varying environment. A series of simplifications were needed to provide a very simple model suitable for applying the Pontryagin's maximum principle. The distance between the proposed optimal strategy and the optimal strategy for a more realistic model is therefore difficult to assess.

When a mathematical model is complex, the application of the Pontryagin's maximum principle is not straightforward. Hence, methods based on numerical optimization are, in practice, the most used. In the standard form, the numerical approach takes place in open loop fashion, without taking into account the real state of the system. For a real implementation, however, available measurements (either online or offline) must be used to compensate for disturbances and to correct model mismatches (see,*e.g.*, [4] for a survey of methods). An example of this type of strategy is the predictive control approach, in which the optimal control problem is solved online. This strategy was developed for the optimization of biomass and oil productivities for the heterotrophic microalgae *Auxenochlorella protothecoides* [11]. This approach, however, is computationally expensive and requires sophisticated algorithms of adaptation and proof of process stability is lacking.

A practical alternative for optimizing system performance is to translate the optimization problem into a regulatory (tracking) problem. The objective then consists in finding a variable (or a combination of variables) that when regulated maintains the system close to optimality [34]. In the case of photobioreactors, the phenomenon of light transfer to the culture governs the performance of the system [28]. Based on this principle, it has been proposed that under constant light, maximal productivities can be attained by maintaining the light intensity at the bottom of the reactor at a constant value. This value corresponds to the compensation irradiance (G_c), defined as the minimum value of light intensity required to guarantee a positive net growth rate (strict compensation condition) [7, 6, 37]. By defining the working illuminated fraction χ as the fraction of the reactor volume with light intensities higher than the compensation irradiance, it has been demonstrated mathematically that an optimal biomass productivity requires the condition $\chi = 1$.

For outdoor raceways, the definition of a strategy to guarantee maximal productivities is not trivial due to the diurnal light cycle. It has been conjectured that the compensation point should also be reached for natural light in order to maximize productivity [25]. Inspired on this premise, an experimental study with *Chlorella sorokiniana* was carried out on an artificial lightened photobioreactor with planar geometry mimicking the daily cycle of light [9]. The experimental set-up was conceived to maintain the photon flux density leaving the reactor at a constant value. The luminostat operation did not exhibit significant improvements of productivity compared to an operation at constant dilution rate. From these results it can be drawn that keeping a constant light intensity at the rear of the reactor might not be an optimal strategy for varying light conditions. Accordingly, an imminent question is thus how to attain maximal productivities when light is varying. In the present work, we proposed a simple operational criterion which when regulated to an adequate set point maintains the system near to optimal operation. The proposed strategy has the advantage to be straightforward to implement in a classical closed loop control.

As a basis, we use the model proposed by [2] for a planar culturing device in combination to a model describing lipid production under nitrogen limitation [19, 20]. These models have shown to reproduce experimental data of lab scale systems. Here, we extend such models to account for characteristics of raceway systems. Our *in silico* case study takes the configuration of a pilot-scale open raceway (Algotron) located at INRA-LBE, France.

2. Modeling

Under the assumption that nitrogen and light are the limiting factors for the growth of microalgae, we combined the biomass model from [2] to the lipid production model proposed in [19, 20]. It results in the following mass balance equations for a completely mixed reactor at constant volume V

$$\dot{s} = f_i s_{in}/V - f_o s/V - \rho x, \tag{1}$$

$$\dot{q_n} = \rho - (\mu - R)q_n, \tag{2}$$

$$\dot{x} = (\mu - f_o/V - R)x, \tag{3}$$

$$\dot{x_l} = \beta q_n \mu x - \gamma \rho x - r_0 \phi_T x_l - f_o x_l/V, \tag{4}$$

$$\dot{x_f} = (\alpha + \gamma)\rho x - r_0 \phi_T x_f - f_o x_f/V, \tag{5}$$

where s is the extracellular nitrogen concentration and q_n is the internal nitrogen quota. The concentration of the total carbon biomass x is the sum of three carbon pools, namely storage lipids (x_l), carbohydrates (x_g) and a functional pool (x_f), mainly formed by proteins and phospholipids. Note that the dynamics of x_g can be easily deduced since $x_g = x - (x_l + x_f)$. The influent nitrogen concentration is s_{in}.

The temperature exerts a strong influence on the behaviour of microalgae systems, in particular in outdoor raceways [27]. This effect is included in the model in two manners. Firstly, it is assumed, in line with [14], that temperature has an homogeneous effect on uptake, growth and respiration rates. Secondly, following the work of [13], the Chl a:N ratio was set to be dependent on the temperature and light. The equations are detailed later on.

To model the growth rate, the following is assumed:

(i) Microalgal growth is uncoupled dynamically to nutrient uptake. Growth kinetics follows the cell quota model of Droop [12].

(ii) Light intensity is distributed spatially in the raceway. The absorption of light in the raceway follows the Lambert-Beer law. Thus, for a given depth z, the corresponding light intensity I_z satisfies

$$I_z = I_0 \exp(-\xi z), \tag{6}$$

where I_0 is the incident light and ξ is the light attenuation factor, expressed as

$$\xi = a\mathrm{Chl} + b. \tag{7}$$

At the bottom of the reactor $z = L$. The term ξL is known as optical depth (λ).

It should be noted that I_0 varies in time in an oscillatory fashion. Its amplitude depends on the season and the geographical location. For a given day, I_0 follows an increasing behaviour until noon, then decreases until midnight.

(*iii*) Light intensity affects the growth rate. This effect is described by a Monod type kinetics. For a given depth z ($0 \leq z \leq L$) with intensity I_z, the growth rate at hypothetical infinite nitrogen quota is

$$\mu_z = \tilde{\mu}\frac{I_z}{I_z + K_{sI}}. \tag{8}$$

Finally, the growth rate is represented by an average growth rate obtained by integration of (8) along the raceway depth. The resulting equation for the growth rate reads

$$\mu = \bar{\tilde{\mu}}\phi_T \left(1 - \frac{Q_0}{q_n}\right), \tag{9}$$

with

$$\begin{aligned}
\bar{\tilde{\mu}} =& \frac{\tilde{\mu}}{\xi L} \ln \frac{I_0 + K_{sI}}{I_0 e^{-\xi L} + K_{sI}}, \\
\phi_T =& \frac{(T - T_{\max})(T - T_{\min})^2}{(T_{\text{opt}} - T_{\min})\left[(T_{\text{opt}} - T_{\min})(T - T_{\text{opt}}) - (T_{\text{opt}} - T_{\max})(T_{\text{opt}} + T_{\min} - 2T)\right]}
\end{aligned} \quad .$$

The term ϕ_T represents the temperature effect. It is described by the model developed for bacteria by [30] and validated for microalgae by [3].

Nitrogen uptake rate (ρ) is modeled by a modified Michaelis-Menten kinetics [19].

$$\rho = \bar{\rho}\phi_T \frac{s}{s + K_s}\left(\nu + (1 - \nu)\frac{\bar{I}^m}{\bar{I}^m + \epsilon_I^m}\right)\left(1 - \frac{q_n}{Q_l}\right). \tag{10}$$

The nitrogen uptake rate is expressed as a function of the average irradiance in the raceway $\bar{I}$. Here, it is considered that nutrient uptake is regulated by the internal nitrogen quota, *i.e.*, when the cells are nutrient saturated, uptake rate stops. Additionally, the equation includes a light regulating factor (in the form of a Hill-type function). Therefore, when the cells enter to the dark period, the nutrient uptake rate exhibits a slowdown.

The model includes an overall respiration rate R, that gathers maintenance respiration and biosynthesis cost (assumed to be proportional to nitrogen uptake rate):

$$R = r_0\phi_T + \varphi\rho, \tag{11}$$

where r_0 is the maintenance respiration and φ is a biosynthesis cost coefficient. Model notation is given in Table 1.

Additionally, it is assumed that chlorophyll concentration (Chl) is correlated to particulate nitrogen (xq_n) [2]. The Chl:N ratio (θ_N) is influenced by light and temperature following [13]

$$\theta_N^{-1} = (g_1 - g_2T) + g_3\bar{I}\exp(-g_4T). \tag{12}$$

In this equation, it is implicitly assumed that the cells are photoacclimated at the average light intensity $\bar{I}$.

Environmental variables, notably light intensity (solar irradiance) and temperature govern reactor performance. These two variables incorporated in the kinetics of growth and nitrogen uptake can be accessible from online sensors or meteorological stations. In addition, mathematical models have been developed to predict light intensity [23] and raceway temperature [1] for a given location. In the present study, mathematical modeling supported by meteorological data was used for the location of Narbonne, France (see Fig. 1).

Model parameters were taken from studies on the microalgae *Isochrysis* aff. *galbana*, when available. The parameters describing ϕ_T are those obtained for *Nannochloropsis oceanica* [3].

3. Driving raceway operation to optimal performance

3.1. Optimal problem statement

In this study, we are interested in designing a control law on the input flow rate (f_i) that allows to bring either the biomass productivity (P_x) or the lipid productivity (P_l) very close to the maximal productivities that can be attained in the raceway. For a given time horizon t_f, the maximal productivities can be obtained by solving an optimal control problem that can be formulated as follows

$$\begin{aligned} &\max_{f_i(t)} \int_{t_0}^{t_f} \psi(t, \mathbf{x}(t), f_i(t))\ dt. \\ &\text{s.t.} \\ &\quad 0 \leq f_i(t) \leq f_{\max} \\ &\quad \dot{\mathbf{x}} = \mathbf{g}(\mathbf{x}, f_i, t),\ \mathbf{x}(0) = \mathbf{x}_0. \end{aligned} \tag{13}$$

With $\mathbf{x}$ the state vector and $f_{\max}$ the upper bound of the input flow rate. If the purpose of the controller is to optimize biomass productivity P_x, then

$$\psi(t, \mathbf{x}(t), f_i(t)) = f_o(t)\ x(t). \tag{14}$$

If the objective is to optimize lipid productivity P_l, then

$$\psi(t, \mathbf{x}(t), f_i(t)) = f_o(t)\ x_l(t). \tag{15}$$

For the sake of clarity, we will call CP_x the optimal controller that maximizes biomass productivity and CP_l the optimal controller that maximizes lipid productivity.

The model equations (1)-(5) were used for the optimization study. The influent nitrogen concentration s_{in} was set to 50 g N m^{-3}. This value is an operational concentration used in Algotron. The volume was assumed to be constant, so $f_o = f_i$.

The Matlab toolbox DOTcvpSB [17] was used for solving the optimal control problems numerically. DOTcvpSB uses the approach of sequential discretization (control vector parametrization) to solve the non-linear programming (NLP) problem. In the optimization stage, the stochatisc algortihms developed by [31] and [36] were used.

3.2. Quasi optimal closed loop control

As it was mentioned in the Introduction section, solving the optimal control problem (13) (with the functional objective defined by (14) or (15)) might be computationally expensive and difficult to implement in practice. For a real implementation, it will be desirable to identify a controlled variable that when regulated towards a set point will ensure that the system operates close to optimality. In this respect and since light transfer

is a crucial phenomenon of the process of microalgal growth, we propose the efficiency of light absorption (η_L) to be such a controlled variable.

$$\eta_L = \frac{I_0 - I_L}{I_0} = 1 - \exp(-\xi L). \tag{16}$$

As it will be shown hereafter, this simple controller has a very good ability to maintain the system close to the optimal solution. In fact, several strategies where tested based on preliminary studies, and η_L turned out to present the best trade-off between simplicity and efficiency.

For a given microalgae, there exists a set point η_L^* that maintains the system near to optimal productivities. The value η_L^* depends on the characteristics of the microalgae, namely optical properties and light affinity. In this study a set point $\eta_L^* = 0.95$ was selected. Note that regulating η_L implies the regulation of the optical depth λ. Given the form of the attenuation factor (7), regulating the optical depth is equivalent to regulating the Chlorophyll concentration. For $\eta_L^* = 0.95$, the set point for Chlorophyll concentration is $\text{Chl}^* = 4.95$ g Chl m^{-3}. This result is very convenient because during darkness the efficiency of light absorption can not be defined but we can still regulate the Chlorophyll concentration to Chl^* in such a way that when $I_0 > 0$ the efficiency of light absorption will be close to η_L^*.

In the following, we show by means of numerical simulation, the performance of the raceway by regulating η_L to the set point η_L^*. This regulation can be achieved by any adequate feedback controller. In this work, we use a standard PI controller. Since our premise is that this controller brings the system to work almost optimally, we call it a quasi optimal (QO) controller.

4. Results

4.1. Comparison of the QO controller to optimal strategy

Figure 2 displays the responses of the state variables and the lipid and biomass productivities (P_l, P_x) when applying the QO controller and the optimal CP_x controller for a time period of 30 days. To calculate the productivities, it was assumed that carbon contributes to the 56% of ash-free dry weight [38]. The productivities are divided by the

surface of the raceway and the time. The QO control controller brings the efficiency of light absorption very close to the defined set point. At $t = 6.5$ d, η_L is 95% of η_L^*. The maximal biomass productivity obtained with the optimal controller CP_x is 168 tons dry weight ha^{-1} a^{-1}. This value is consistent with productivities reported in the literature [5, 38]. Importantly, the biomass and lipid productivity provided by the QO controller were both 98% of those given by the controller CP_x (Table 2). After 25 d, the final lipid quota ($q_l = x_l/x$) oscillates with a maximal value of 16%. This relative low level of lipids is due to the fact that many of the parameters used in the model were taken from studies with *I. galbana*, which is known to have a low lipid content.

To have an assessment of the maximal lipid productivity that can be attained, the optimal controller CP_l was calculated. For the model parameters used in our case study, it resulted that optimizing lipid productivity was equivalent to optimizing biomass productivity. Thus, the response of the system behaviour when applying the CP_l controller was very similar to the response obtained when applying the CP_x controller. This result is interesting because it is often claimed the conflict between optimizing lipid productivity and optimizing biomass productivity. Indeed, such a conflict occurs when light is constant. Figure 3 shows the system response for the optimization of the two performance indexes (P_x, P_l) when the system was set to operate at constant temperature (21°C) and constant incident light (250 μmol photons $m^{-2}s^{-1}$). It is observed that while the optimal strategy for biomass productivity provides a higher biomass concentration, the optimal strategy for lipid productivity drives the microalgae to increase its lipid content, which in turn is detrimental for attaining high concentration of biomass. While the difference between the biomass productivities obtained by the two controllers is very small, the CP_l controller provides a lipid productivity that is 10% higher than that obtained with the CP_x controller. These differences may become more important for microalgae with high potential of lipid accumulation.

For a diurnal light cycle, however, our results suggest that there is not discrepancy between optimizing lipid productivity and optimizing biomass productivity. For both performance indexes, the cells should growth as much as they can in the light period to accumulate enough carbon. The higher the biomass the concentration, the higher

the available carbon source that can be potentially directed to the lipid pool. To assess whether our indication was independent on the properties of lipid accumulation of the microalgae, the coefficients of fatty acid synthesis (β) and fatty acid mobilization (γ) were modified to represent a microalgae with high lipid level ($\approx$ 40% of the total carbon). The optimal controllers CP_x and CP_l were further calculated with the new parameters. The system dynamics were specific to each applied controller CP_x and CP_l, *e.g.*, the biomass concentration for the CP_x exhibited a different dynamics that the biomass concentration provided by the CP_l. However, such differences were not significant and both controllers provided similar biomass and lipid productivities. Hence, we confirm the previous suggestion that optimizing lipid productivity is almost equivalent to optimizing biomass productivity for a photobioreactor with diurnal light cycle.

The results presented here are very promising. We show that the QO controller performs as well as the optimal controllers, confirming our hypothesis that controlling the efficiency of light absorption (η_L) makes it possible to attain high productivities both in lipid and biomass. The response of the QO controller suggests that an optimal strategy consists in driving the biomass concentration to a certain value and to allow it oscillate around this point. This result is consistent with the work developed by [6] and the theoretical results presented by [16], where an optimal controller was developed by forcing the biomass concentration to fulfill a periodicity condition.

4.2. Comparison of open loop configurations to optimal strategy

We were interested to assess the performance of the raceway in open loop (OL) configuration. To this end, the model was simulated initially with an input flow rate $f_i = 5.13$ $\mathrm{m}^3\ \mathrm{d}^{-1}$ (dilution rate $\mathrm{D} = 0.30\ \mathrm{d}^{-1}$), which is a typical value [5, 22]. The lipid and biomass productivities were, respectively, 54% and 59% of those obtained with the optimal controllers CP_x and CP_l. This means that for an open loop configuration, a wrong choice of the input flow rate will imply an unsatisfactory performance. To perform a fair comparison, in addition to the optimal controllers previously calculated, the optimal control problem (14) was solved by setting a constant flow rate. The optimal flow rate was found to be 3.22 $\mathrm{m}^3\ \mathrm{d}^{-1}$ ($\mathrm{D} = 0.19\ \mathrm{d}^{-1}$) and the resulting biomass productivity was 93% of the

one obtained with the optimal controller CP_x. Table 2 summarizes the comparison of the performances of different controllers and configurations evaluated (including the QO controller) relative to the optimal productivities. Additionally, Fig. 4 shows the dependency of the biomass and lipid productivities on the dilution rate. The curves are normalized to illustrate that the both productivities reach their maximal value at the same dilution rate.

The relative high productivity obtained with the optimal constant flow rate is not surprising, since experimental studies on artificial photobioreactors [9, 10] have shown that with an adequate constant flow rate it is possible to attain high productivities. This result may suggest that, when the microalgae are not nutrient limited, the environmental conditions, namely light intensity and temperature exert such a strong influence on the system behaviour that the improvement of the performance that can be reached by manipulating the dilution rate is only marginal. This finding might, at first sight, discourages the endeavour of developing any control strategy for raceways systems, since it appears that even with a constant flow rate, a satisfactory performance can be attained. This result, however, must be taken with caution. Indeed, we argue in favor of the QO controller over the other control strategies and, of course, over open loop operation. The arguments supporting our decision are developed in the following.

4.3. Robustness of optimal strategies and QO controller

The previous results that indicate that an adequate constant flow rate leads to near optimal operation are derived from very well controlled systems (closed photobioreactors) or from mathematical models that do not take into account model uncertainty and potential disturbances. Since the QO controller operates in closed loop fashion, it has many practical advantages. For instance, it can be easily tuned for a real scenario that is subjected to disturbances and technical failures. The optimal controllers can also be in closed loop fashion. However, its implementation is more demanding than that of the QO controller. If the optimal controllers are used in open loop, the system can be directed to suboptimal operation. Figure 6 displays the productivities given by the QO controller and the optimal controller CP_x considering uncertainty in the model parameters. The value

of $\tilde{\mu}$ was decreased 30% of the value used originally to calculate the optimal controller. It is observed that the QO controller provided a biomass productivity that is 17% higher than that provided by the controller CP_x. It should be noted that this result was achieved with a simple PI controller. We expect that by using a nonlinear controller based on the ligth efficiency, the productivity might be even better. The design of such a nonlinear controller is one of the perspectives of this work.

4.4. Is the strict compensation condition relevant for diurnal light cycles?

The strict compensation condition (implying that the working illuminated fraction $\chi = 1$) has been identified as a necessary condition to attain maximal productivities in closed photobioreactors under light constant regime [37]. The light intensity at which the compensation occurs is often expressed as a constant parameter. Indeed, if the incident light intensity is constant, there exists one value of light intensity at the bottom of the reactor at which the productivity is maximal [21]. However, we might notice that for a varying light system, the light of compensation depends on the actual state of the system and thus there is not a fixed value that will bring the system to operate under the strict compensation condition.

For outdoor raceways, where microalgae are exposed to long periods of darkness, respiration affects negatively growth. It is clear that in the dark period, the compensation condition do not play any role on the reactor performance. When the incident light is higher than zero, the strict compensation condition is such that $\mu_L = R$. The light of compensation is thus a dynamic operational variable that depends of the state of the system. The optical depth of the reactor must then be adjusted accordingly to reach the light of compensation at the rear of the reactor. Note that if the reactor volume is constant, the regulation acts on the attenuation factor ξ. This strategy, however, may suffer of reachability problems, as experienced in the study of [9], where the light at the bottom of the photobioreactor could not be maintained at the defined set point due to the dynamic boundary imposed by the growth rate. To enlarge the discussion in this point, we assess by means of simulations if the strict compensation condition could be fulfilled in a diurnal light cycle and if it is relevant to attain such a condition to achieve maximal

productivities. The following optimal control problem was defined

$$\min_{f_i(t)} \int_{t_0}^{t_f} (\mu_L - R)^2 \, dt. \tag{17}$$

The controller optimizing (17) is called CP_c.

Figure 5 shows the ratio between the growth rate at the rear of the raceway (μ_L) and the respiration rate (R). The results are given for the optimal controller CP_c. It is observed that, for the light period, the growth rate at the rear of the raceway is higher than the respiration rate and that the compensation condition is not strictly fulfilled all the time $\chi > 1$. The results indicate that attaining the strict compensation throughout the day might be no physically possible due to the dynamic bound imposed by the growth rate.

The optimal controller CP_c resulted in biomass and lipid productivities that were, 100% of those obtained with the optimal controllers CP_x and CP_l. Our results suggest that the closest the system is to the compensation condition the closest the system operates optimally. However, the results also indicate that for a photobioreactor subject to the diurnal light cycle, the strict compensation condition is not a necessary condition to be fulfilled for achieving maximal productivities. We have also verified that trying to impose a compensation condition valid around the midday light peak could be inefficient resulting in low productivities.

We must note that when the respiration rate is very low, the strict compensation condition became $\mu_L \approx 0$ implying that $I_L \approx 0$. Here, the compensation condition implies almost full absorption of light which is rather difficult to maintain throughout the day. Due to the limitation of reachability of the strict compensation condition and the difficulty associated to the online determination of μ_L and R, we suggest that the strict compensation condition is not a practical criterion for the design of control strategies. By contrary, the strategy that we proposed of controlling the efficiency of light absorption η_L is technically feasible for real implementation and provides almost optimal productivities. In the near future, an optimal framework of harvesting strategies will be proposed complementary to the QO control.

5. Conclusion

To summarize, controlling the efficiency of light absorption makes it possible to attain maximal productivities. The overall performance of the QO controller developed here and its practical advantages for real implementation makes it a suitable control strategy for optimizing microalgae production in raceways.

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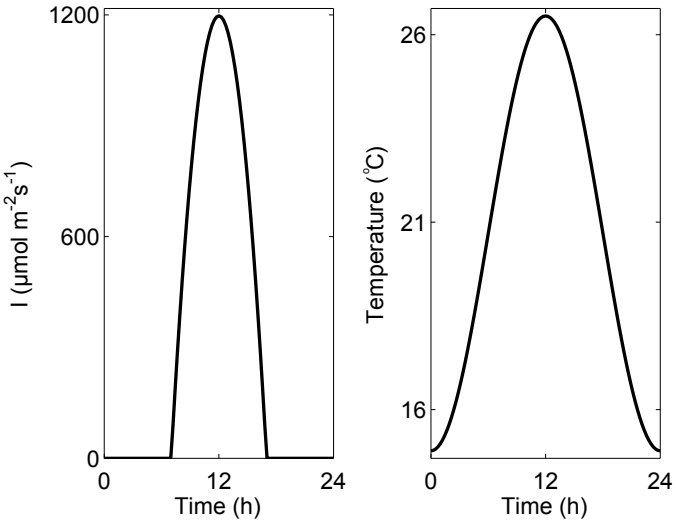

Figure 1: Typical diel variation of light intensity and temperature for the location of Narbonne in June.

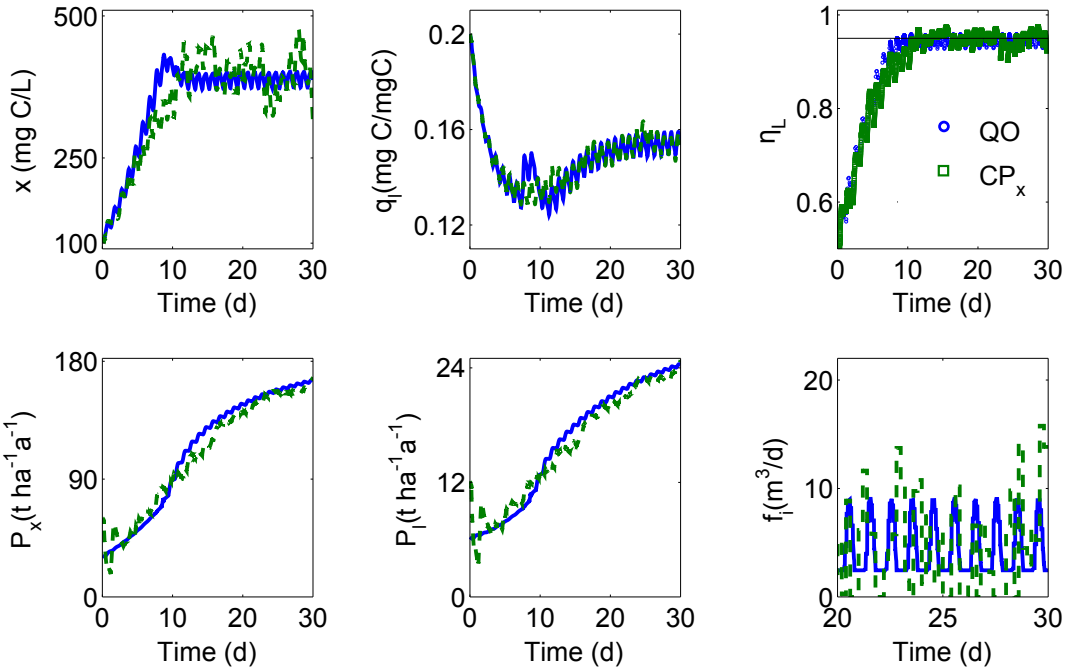

Figure 2: Trajectories of state variables and productivities given by the QO controller (solid blue line) and by the optimal controller CP_x (dashed green line). The productivities are given in dry weight basis. The biomass and lipid productivities given by the QO controller are both 98% of those provided by CP_x. The top right plot shows the evolution η_L during the light period. The horizontal continuous line corresponds to the set point $\eta_L^* = 0.95$.

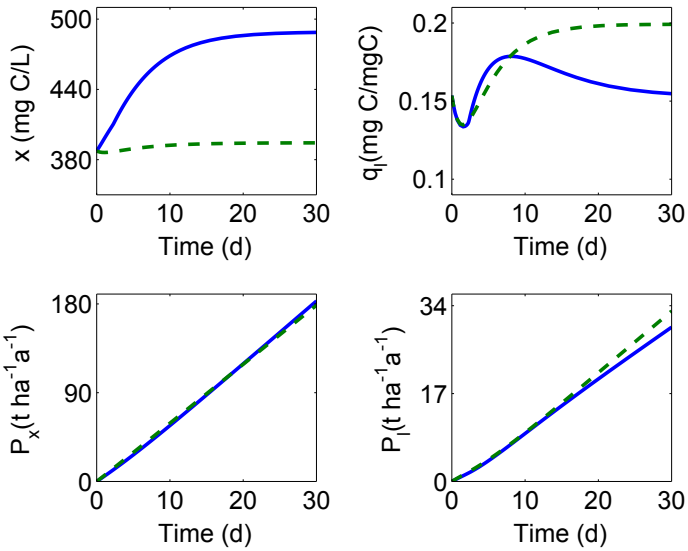

Figure 3: In a photobioreactor with constant incident light, the response of the system when applying a controller to optimize lipid productivity (dashed green line) differs of the response provided by a controller optimizing biomass productivity (solid blue line). Maximizing biomass productivity favors high biomass concentration, while maximizing lipid productivity favors high lipid quota.

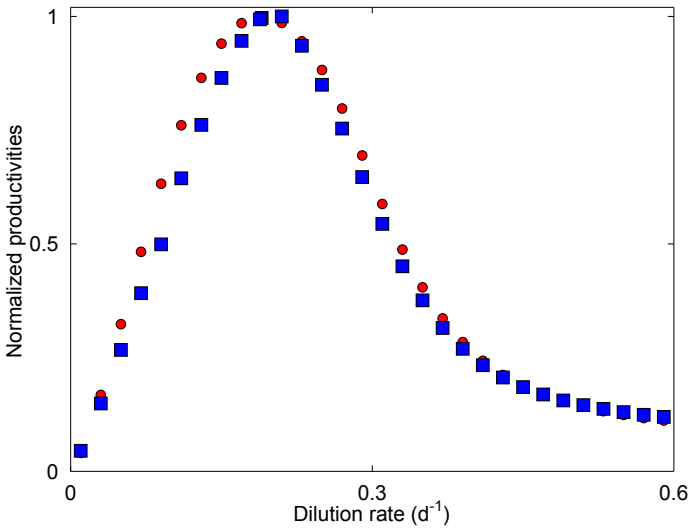

Figure 4: Normalized productivities at different dilution rates. In a raceway reactor, the biomass productivity (circles) and the lipid productivity (squares) reach their maximal value at almost the same dilution rate.

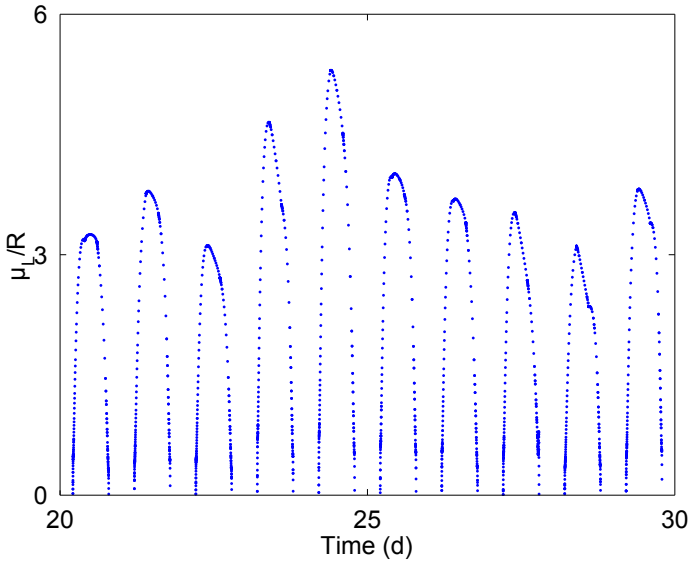

Figure 5: The strict compensation condition (μ_L/R=1) is not attained along the day. Response obtained for the optimal controller CP_c.

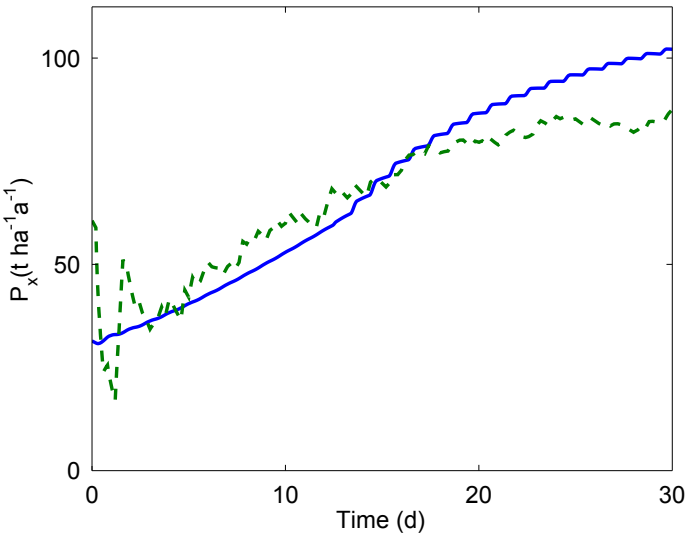

Figure 6: Productivities provided by the QO controller (solid blue line) and the optimal controller CP_x (dashed green line) under parameter uncertainty. The value of $\tilde{\mu}$ was decreased 30%.

Table 1: Model notation and parameter values.

	Definition	Units	Value
Variables			
s	Nitrogen concentration	g N m^{-3}	
q_l	Neutral lipid quota	g C (g C)$^{-1}$	
q_n	Nitrogen quota	g N (g C)$^{-1}$	
x	Carbon biomass concentration	g C m^{-3}	
x_f	Functional carbon concentration	g C m^{-3}	
x_g	Carbohydrates carbon concentration	g C m^{-3}	
x_l	Lipid carbon concentration	g C m^{-3}	
Chl	Chlorophyll concentration	g Chl m^{-3}	
G_c	Compensation light intensity	μmol photons $m^{-2}s^{-1}$	
I_0	Incident light intensity	μmol photons $m^{-2}s^{-1}$	
$\bar{I}$	Average light intensity	μmol photons $m^{-2}s^{-1}$	
I_L	Light intensity at the bottom of the raceway	μmol photons $m^{-2}s^{-1}$	
I_z	Light intensity at depth z	μmol photons $m^{-2}s^{-1}$	
T	Raceway temperature	°C	
Functions and parameters			
χ	Working illuminated fraction		
η_L	Efficiency of light absoprtion		
ϕ_T	Temperature factor affecting growth kinetics		
λ	Optical depth		
μ	Growth rate	d^{-1}	
$\bar{\bar{\mu}}$	Average growth rate	d^{-1}	
ρ	Nitrogen uptake rate	g N (g C d)$^{-1}$	
θ_N	Chl:N ratio	g Chl (g N)$^{-1}$	
ξ	Attenuation factor	m^{-1}	
D	Dilution rate	d^{-1}	
f_i	Feeding flow rate	m^3 d^{-1}	
f_o	Effluent flow rate	m^3 d^{-1}	
f_r	Rain flow rate	m^3 d^{-1}	
f_v	Evaporation flow rate	m^3 d^{-1}	
R	Overall respiration rate	d^{-1}	

α	Protein synthesis coefficient	g C (g N)$^{-1}$	3.0
β	Fatty acid synthesis coefficient	g C (g N)$^{-1}$	3.80
ϵ_I	Dissociation light constant.	μmol photons m^{-2}s^{-1}	50
φ	Biosynthesis cost coefficient	g C (g N)$^{-1}$	1.30
γ	Fatty acid mobilization coefficient	g C (g N)$^{-1}$	2.90
ν	Reduction factor of nitrogen uptake during night		0.19
$\tilde{\mu}$	Theoretical maximum specific growth rate	d^{-1}	2.11
$\bar{\rho}$	Maximum uptake rate	g N (g C d)$^{-1}$	0.10
a	Light attenuation due to chlorophyll	m^2(g Chl)$^{-1}$	2.0
b	Light attenuation due to background turbidity	m^{-1}	0.087
g_1	Coefficient Eq. (12)	g N (g Chl)$^{-1}$	16.74
g_2	Coefficient Eq. (12)	g N (g Chl °C)$^{-1}$	0.39
g_3	Coefficient Eq. (12)	g N (g Chl μmol photons m^{-2}s^{-1})$^{-1}$	0.0014
g_4	Coefficient Eq. (12)	(°C)$^{-1}$	0.0015
K_s	Nitrogen saturation constant	g N m^{-3}	0.018
K_{sI}	Light saturation constant	μmol photons m^{-2}s^{-1}	150
L	Pond depth	m	0.30
m	Hill coefficient		3.0
Q_l	Saturation cell quota	g N (g C)$^{-1}$	0.20
Q_0	Minimal nitrogen cell quota	g N (g C)$^{-1}$	0.05
r_0	Maintenance respiration rate	d^{-1}	0.01
s_{in}	Influent nitrogen concentration	g N m^{-3}	50
S	Pond surface	m^2	57
$T_{\min}$	Lower temperature for microalgae growth	°C	-0.20
$T_{\max}$	Upper temperature for microalgae growth	°C	33.30
T_{opt}	Temperature at which growth rate is maximal	°C	26.70
V	Raceway volume	m^3	17.10

Table 2: Productivity performance of open loop (OL) configuration and closed loop controller. The resulting performance is presented relative to the optimal strategy.

	$100\mathrm{P}_x/\mathrm{P}_x^*$	$100\mathrm{P}_l/\mathrm{P}_l^*$
QO	98%	98%
CP_c	100%	100%
OL: $f_i^\star = 3.22$ m^3 d^{-1}	93%	91%
OL: $f_i = 5.13$ m^3 d^{-1}	54%	59%

* stands for the productivities obtained by the optimal controllers CP_x and CP_l. $\star$ optimal constant flow rate.